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Food Calorie Estimation Using Deep Learning Neural Network

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Abstract- As food becomes more accessible, the prevalence of obesity is rising, which is a serious chronic disease. Maintaining good health requires precise monitoring of caloric intake. Traditional methods, nevertheless, could be tedious and wasteful. Calorie estimation from food photos using deep learning neural networks is the subject of this research. We provide a technique that analyses food images using Deep Neural Network (DNN) to calculate calorie content. Deep Neural Network (DNN) is with 22 layers to accurately identify the food in the system. A massive collection of tagged food pictures with calorie information is used to train the DNN. As part of the training process, the model extracts shape, colour, and texture information from the images, and then converts it to calorie content. One of the many advantages of this technology is that it provides calorie estimates more efficiently and without invasiveness than manual methods. To further assist with dietary tracking and weight management goals, it may also be integrated with mobile applications. Properly evaluating calorie content for complex recipes with several components is difficult, and obtaining high-quality and diverse training data to avoid bias is another difficulty. When compared to the state-of-the-art method, the suggested approach performs better.

Keywords- Food Calorie, DNN, Food Segmentation

I. INTRODUCTION

The development of technology has led to an increase in the awareness of people about the things that they consume in order to satisfy their desires. Recent years have seen an increase in the prevalence of obesity, which is the reason for this tendency. There were about 1.9 billion people (aged 18 and older) in the globe who were overweight in 2016, with 650 million of them being obese, as stated by the globe Health Organization (WHO) [1]. In 2018, there were forty million children under the age of five who were overweight, which is a trend that is cause for worry around the world. There were around 38.2 million children under the age of five who were either overweight or obese in the year 2019. In recent years, there has been a rise in the prevalence of obesity among younger people. The prevalence of chronic diseases like heart disease, stroke, diabetes, liver problems, kidney damage, and countless more is directly correlated with the increased consumption of fast food and other junk foods among young people, especially children, who are more influenced by western lifestyle, the internet, and television ads. [2] and [3]. The practice of keeping a food diary has become more popular as a means for people to monitor the number of calories they should consume at any given time in order to stay away from these problems. Not only is there the concept of digital journaling, but there is also the idea of utilizing smartphones or cameras to identify meals and estimate the number of calories they contain. On the other hand, it raises a great deal of uncertainty due to the fact that there are several varieties of food pictures that originate from a variety of cuisines all over the world. As a result of the scientists' years of research and inquiry, they have provided us with a number of different hypotheses on this topic. The majority of the systems that are now available have a limited ability to accurately recognize meal components, much alone show the total predicted calories.

Image identification of food calories is significant for a number of reasons, including the following:

1. Nutritional Awareness
Having an understanding of calories enables customers to make informed choices about their diets by providing them with essential information on the nutritional worth of food.

When it comes to maintaining a balanced diet, those who are able to detect the calorie content of foods from Images may have a better understanding of the energy value of their meals and be able to better control the amount of calories they consume.

2. Health Management
Keeping a record of the number of calories you consume is essential for achieving your weight reduction or maintenance objectives. The identification of food calories from images enables users to more easily keep track of the number of calories they consume on a daily basis, which simplifies the process of controlling their weight and encourages good eating habits.

3. Dietary Planning
Being aware of the calorie content of various meals is beneficial when it comes to meal planning and administering appropriate portions. People who are wanting to lose weight, build their muscle mass, or improve their overall health may find that having access to knowledge about calories may assist them in developing well-balanced meal plans that are tailored to their specific nutritional needs and dietary goals for nutrition.

4. Personalized Nutrition
Image-based calorie detection has the potential to be integrated into apps or services that provide tailored nutrition. These systems are able to deliver individualized recommendations and nutritional support to users by evaluating their eating patterns and trends in calorie consumption. These recommendations and assistance are based on the users' tastes and goals.

II. LITERATURE SURRVEY

Over the course of the early stages of research, the majority of studies, including [4] and [5], used standard Machine Learning (ML) algorithms in order to ascertain the nutritional worth of food photos. On the other hand, we have seen a pattern in the utilization of frameworks that are based on Deep Learning (DL) since the year 2014 [7], [8]. In recent times, academics have been using several optimization strategies, including the Genetic Algorithm (GA) [9], Fuzzy Clustering for data filtering [6], and Particle Swarm Optimization (PSO) [9]. During the year 2019, Min et al. [10] conducted a study on the computation of food. In their review, they included a broad variety of subjects, such as the development of food datasets, the perception of food, the identification of food, the retrieval of food data, the recommendation of food, and the prediction and monitoring of societal problems. An analysis of the existing literature on food image datasets, segmentation, item classification, and volume estimation was carried out by Subhi et al. [11]. They examine feature selection, traditional machine learning methodologies, and Deep Learning techniques in the portion that is devoted to the classification of beverages. The article by Amugongo et al. [12] from 2023 highlights the potential of mobile computer vision-based applications for measuring the amount of food consumed on a daily basis.an image-based calorie estimating approach was proposed by P. Kumar et al. [13]. This method involves the user uploading a Image of a food item, and then the estimated number of calories contained in the image is determined. Using Images of food, B. Senapati and colleagues [14] develop a method for detecting and identifying individuals who have food allergies. The transfer learning model known as ResNet50 was trained to identify the kind of food, validate the label that was discovered, and deliver the nutrients that were included in the food 101 dataset.

The sheer amount of different food possibilities is mind-boggling. Food diversity in general. The term "food" encompasses a wide range of shapes, sizes, colours, and textures, including anything from simple fruits and vegetables to intricate dishes from different ethnic cuisines. Because of this, it is difficult for image recognition algorithms to generalize their knowledge and accurately identify different types of food, especially when they are presented with unfamiliar items.

1. Visual Ambiguity

Even within the same food category, there may be a great amount of variation in overall look. For instance, a chicken breast that has been grilled may take on a variety of different looks depending on the method of cooking, the seasoning, and the amount of presentation taken. This visual ambiguity makes it difficult to appropriately relate certain visual aspects to calorie counts. calorie counts are calorie counts.

2. There is a possibility that estimating the amount of a serving from an image might be difficult, even after correctly recognizing the food item. It is possible for large size estimation discrepancies to be caused by a variety of factors, including camera angle, plate size, and overlapping objects. These factors have a direct impact on the estimates of calories.

3. The complexity of the contents

Many foods have a large number of ingredients, each of which has its own percentage of calories. It is a challenging technique that involves proficient image segmentation as well as an understanding of the composition of food in order to extract particular components and the amounts of those components from a Image.

4. Data Challenges

In order to train powerful image recognition models, they need vast amounts of labelled data, which may be difficult to gather and assess due to the fact that it can be both expensive and time-consuming. In addition, the wide diversity of foods makes it difficult to construct datasets that are completely representative and take into account every potential case.

Food calorie detection has the potential to offer several benefits, making it valuable in various contexts.

Diet Tracking and Management

By easily tracking calorie intake through pictures, people can gain a better understanding of their daily consumption and make informed dietary decisions. This can be helpful for weight management, managing pre-existing health conditions, and optimizing athletic performance.

Food Awareness and Education

Recognizing what you eat and its calorie content can lead to more mindful eating habits and informed choices. This can contribute to building a healthier relationship with food and promoting balanced nutrition.

Automation and Personalized Recommendations

Advanced systems could automatically suggest healthier alternatives based on individual calorie goals and preferences.

Despite these challenges, researchers are actively developing new approaches for food calorie estimation from images. Techniques like deep learning and computer vision are showing promising results, and with continued research and development, we can expect more accurate and reliable calorie estimation tools in the future. It's important to note that current food calorie detection technologies are still under development and have limitations. Accuracy can vary depending on factors like image quality, food variety, and portion size. Additionally, relying solely on automated calorie information without considering other nutritional factors is not recommended for comprehensive dietary planning. However, the potential benefits and ongoing research efforts suggest that food calorie detection will continue to evolve and become a valuable tool for supporting personal health, improving food systems, and advancing dietary research.

III. METHODOLOGY

Several applications that deal with image processing often make use of convolutional neural networks, also known as CNNs. The neurons that make up these structures are capable of learning weights and biases. The activation function is used after each neuron has received a large number of inputs, computed a weighted sum, and then used. Pooling and convolution are the two primary functions that may be used in this particular situation. It is assumed by convolution that nearby pixels are tightly connected to one another. For the purpose of calculating the dot product between the kernel and the section of the image that is covered by the kernel, a kernel is dragged over the whole picture. A large number of kernels may be found in each phase, which is not only possible but also rather common. Each successive step results in an increase in the total number of layers. It is necessary to make use of pooling layers in order to avoid dimensionality growth. They do their operation on each layer separately, merging pixels that are next to one another into a single cell.

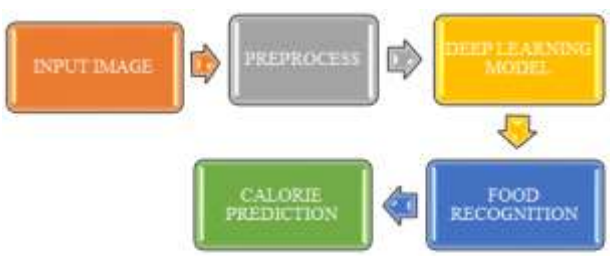

Figure 1: Proposed Architecture

Applying a Deep Neural Network, also known as a DNN, is an approach that shows promise for estimating the number of calories contained in food based on photos. The ability of deep neural networks (DNNs) to learn complex patterns from visual input might potentially result in more accurate calorie estimations than those obtained using standard methods.

It is possible for the model to adapt to a wide range of food types and cuisines if it is given adequate training and access to large datasets. In general, the DNN-based food calorie estimate has a good deal of promise for revolutionizing the monitoring of dietary intake. Nevertheless, it is essential to be aware of its limitations and to use it as a tool for mindful eating rather than as a calorie counter that can be relied upon consistently.

Following is a list of the most important elements and enhancements that the suggested model possesses:

1. To begin, the beginning

The module is the component that functions as the design's base. Several parallel convolutional routes with different kernel sizes (1x1, 3x3, and 5x5) are used to gather characteristics at different spatial scales. These pathways are made up of a large number of layers.

Concatenating the outputs of the pathways in a depth-wise fashion results in the formation of the module's final output. Because of the presence of a large number of parallel routes, the network is able to efficiently gather data from both local and global sources, which ultimately leads to superior representation learning.

2. Global Average Pooling

This technique is used at the end of the network rather than the more common practice of using layers that are totally connected together.

Through the use of global average pooling, the average of each feature map is computed over all spatial dimensions, resulting in a feature vector of fixed length that is independent of the overall size of the input. Through the use of global average pooling, the number of parameters in the network may be reduced while simultaneously limiting overfitting, which ultimately leads to improved generalization performance.

3. Auxiliary Classifiers

The model that has been developed includes auxiliary classifiers that are attached to network intermediate layers when the training is taking place. Through the transmission of additional supervision signals to lower layers, these auxiliary classifiers contribute to the mitigation of the vanishing gradient problem. The final loss is determined by combining the outputs of these auxiliary classifiers with the output of the main classifier that was used during the training process.

The suggested model is a deep neural network with 22 layers (27 levels with auxiliary classifiers). The architecture of the deep network is described in the next paragraph. By lowering the dimensionality of the data via the use of 1x1 convolutions and making the most efficient use of the parameters in the Inception modules, it is able to achieve computational efficiency despite its depth.

4. Training and Optimization

Through the use of supervised learning, the proposed model was trained using the ImageNet dataset, which consists of millions of annotated Images spanning hundreds of categories.

The training of the network was accomplished via the use of stochastic gradient descent (SGD), which included momentum and weight decay regularization. For the purpose of increasing the variability of the training samples and the generality of the results, data enrichment techniques such as random cropping, horizontal flipping, and colour jittering were utilized.

At the time of its first introduction, Deep Net achieved state-of-the-art performance on the ImageNet dataset, which is evidence that the Inception architecture is beneficial for image classification applications. Over the course of subsequent study, it has given rise to a number of different adaptations and changes, which has led to advancements in deep learning for computer vision.

IV. EXPERIMENT & RESULTS

Testing on the recommended DEEPNET framework required the usage of a well-designed dataset. Such a dataset should also have a decent collection of hyperparameters, as well as a set of hardware resources for training. The techniques for each of the tests that were performed based on these criteria are described in the sections that follow.

True Positive (TP)

Total correctly retrieved samples of current class (out of 100)

True Negative (TN)

Total correctly retrieved samples of remaining class (out of 900)

False Positive (FP)

Total incorrectly retrieved samples of current class (out of 100)

True Negative (TN)

Total correctly retrieved samples of remaining class (out of 900)

Accuracy

- Accuracy=[TP + TN]/ [P + N]
- Fall-out or false positive rate (FPR)
- FPR=[FP] / [N]
- Specificity , selectivity or true negative rate (TNR)
- TNR=[TN] / [N]
- Sensitivity, Recall, Hit Rate, Or True Positive Rate (TPR)
- TPR=[TP] / [P]

Figure 2: Accuracy Comparison of Proposed method

Proposed Deep Dense Network achieves 95 % accuracy while other ResNet50 achieves 93% respectively

As you are aware, when a machine learning model is used to forecast, it has a specific level of recall (or confidence).

This arises because the machine learning model constantly predicts that each sample belongs to a certain class. As a consequence, the false negative will equal zero. On the other hand, in this case, the number of erroneously classified samples (f p) would be high, resulting in low accuracy.

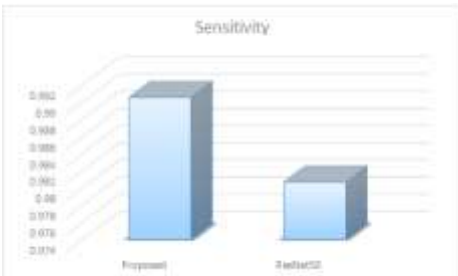

Figure 3: Sensitivity Comparison of Proposed method

Proposed Deep Dense Network achieves 99 % sensitivity while other ResNet50 achieves 98% respectively

Figure 4: Specificity Comparison of Proposed method

Proposed Deep Dense Network achieves 98 % Specificity while other ResNet50 achieves 95% respectively

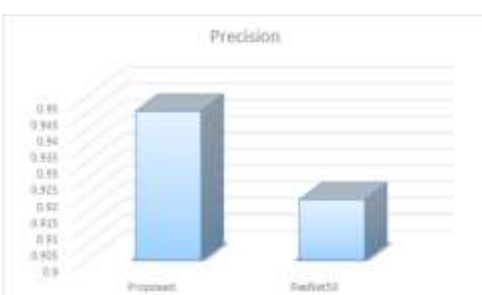

Figure 5: Precision Comparison of Proposed method

Proposed Deep Dense Network achieves 94 % precision while other ResNet50 achieves 91% respectively

V. CONCLUSION

Instantaneous estimation of food nutrition value from the food images is critical for multiple classes of people including pre-diabetic and pre-obese people, specially who are at lifelong risk of diabetes and obesity, and elderly people who are at risk of malnutrition. For all of them, quality of life is at stake.

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